Psychological Barriers in Three Markets with Different Profiles: ADR, ETF and Cryptocurrencies

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Biographical Note

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Abstract

Behavioral Finance studies how economic agents' decisions deviate from what is expected by traditional finance and the consequences of having agents whose decisions are not completely rational, recurring to the knowledge of other sciences, especially Psychology.

Psychological barriers are one of the hot topics in Behavioral Finance, having been widely studied since the 1990s. Works have been published proving or disproving the existence of psychological barriers in financial assets such as stock indices, single stocks, bonds, commodities and derivatives, in the most diverse geographies.

Our work aims to extend the study of this phenomenon to unexplored assets and markets, namely American Depositary Receipts, Exchange-Traded Funds and Cryptocurrencies. To do so, we follow the methodology of Aggarwal and Lucey (2007), performing uniformity, barrier hump, barrier proximity and conditional effects tests to diversified samples composed by the daily closing quotes of six of the most liquid assets of each market for the 10-year period between 2008 and 2017, subsequently assessing if psychological barriers exist in each of those markets. Additionally, we compare the results and conclusions obtained for each financial market and relate them to the profile of the more prominent investors in each market, assessing if there are significant differences in the susceptibility of each type of investor to the biases which cause psychological barriers.

We find that psychological barriers exist in each of the three studied markets but occur more frequently in the cryptocurrencies market, which has a predominance of individual investors. These results indicate that, even though all investors are susceptible to psychological barriers, individual investors are more prone to the behavioral biases which cause those barriers than institutional investors.

Key-words: psychological barriers; american depositary receipts; credit default swaps; exchange-traded funds; cryptocurrencies.

JEL codes: G14; G15; G41

Resumo

As Finanças Comportamentais estudam o modo como as decisões dos agentes económicos diferem daquilo que é esperado pelas Finanças tradicionais e as consequências da existência de agentes cujas decisões não são completamente racionais, recorrendo ao conhecimento de outras ciências, especialmente da Psicologia.

As barreiras psicológicas são um dos pontos mais debatidos das Finanças Comportamentais, tendo sido amplamente estudadas desde os anos 1990. Foram publicados estudos confirmando ou desmentindo a existência de barreiras psicológicas em ativos financeiros como índices, ações, obrigações, mercadorias e derivados, nas mais diversas localizações geográficas.

O nosso trabalho pretende estender o estudo deste fenómeno a ativos e mercados ainda não explorados, nomeadamente *American Depositary Receipts, Exchange-Traded Funds* e Criptomoedas. Para esse efeito, seguimos a metodologia de Aggarwal e Lucey (2007), aplicando testes de uniformidade, barreiras e efeitos condicionais a amostras diversificadas compostas pelas cotações diárias de fecho de seis dos ativos mais líquidos de cada mercado para o período de 10 anos entre 2008 e 2017, avaliando assim se existem barreiras psicológicas em cada um desses mercados. Adicionalmente, comparamos os resultados e conclusões obtidos para cada mercado e relacionamo-los com os respetivos perfis de investidores, com o intuito de avaliar se existem diferenças significativas na suscetibilidade de cada tipo de investidor aos *biases* que constituem causas das barreiras psicológicas.

Descobrimos que as barreiras psicológicas existem em cada um dos três mercados estudados, mas ocorrem mais frequentemente no mercado das criptomoedas, que é predominado por investidores individuais. Estes resultados indicam que, ainda que todos os investidores sejam suscetíveis às barreiras psicológicas, os investidores individuais são mais propensos aos *biases* comportamentais que causam essas barreiras do que os investidores institucionais.

Palavras-chave: barreiras psicológicas; *american depositary receipts; exchange-traded funds*; criptomoedas.

Códigos JEL: G14; G15; G41

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1 Introduction

Psychological Barriers are currently one of the most important topics of investigation in the field of Behavioral Finance, with several empirical studies published since the 1990's, proving or disproving the existence of psychological barriers in a variety of financial markets, such as stock indices, single stocks, bonds, derivatives and gold, among others. However, there is still a wide array of relevant financial markets which lack a study of psychological barriers.

The main aim of our work is to extend the study of psychological barriers to the markets of American Depositary Receipts, Exchange-Traded Funds and Cryptocurrencies, verifying the existence or absence of price barriers in those markets. This study is the first, at least to our knowledge, studying this anomaly in the markets referred above, thus adding a relevant contribution to the field of Behavioral Finance and particularly to the study of psychological barriers. Additionally, our work has the peculiarity of studying financial markets with significantly different investor profiles, through which we aim to analyze which investors are affected by the biases that can cause the existence of psychological barriers.

We start our work with a thorough literature review, dwelling on brief definitions of ADR, ETF and cryptocurrencies, the relevance and recent evolution of each studied market and the different investor profiles of each of them, a historical overview about market inefficiency and psychological barriers, a list of plausible causes of psychological barriers, as well as the previous empirical studies and the respective conclusions about the existence or absence of price barriers in each of the already studied markets.

Following that literature review, our study will analyze if psychological barriers exist in each market, with a sample composed by six of the most liquid assets from the respective financial market, chosen with the concern of providing a diversified sample.

We collect the daily quotes of each of these assets for the period between January 1, 2008 and December 31, 2017. For the assets whose first trading day was after January 1, 2008 – namely the Alibaba ADR, the Germany ETF and all cryptocurrencies – the start date of our sample corresponds to the first trading day of the asset.

Then, we apply to our sample the same methodology as Aggarwal and Lucey (2007), which includes a uniformity test, a barrier proximity test, a barrier hump test and a conditional effects test. The uniformity test is performed so we can evaluate if all M-values present the same frequency; the barrier proximity test allows us to assess if observations on or near a barrier occur significantly less frequently than what would be predicted by a uniform distribution; the barrier hump test analyzes the whole shape of the M-values distribution and finally the conditional effects test intends to understand the market behavior before and after crossing a barrier, either from above or from below.

Our results show evidence of the existence of psychological barriers for the Vale ADR, the Brazil and Germany ETFs and four cryptocurrencies: Bitcoin, Dash, NEM and Ripple. The observation that the cryptocurrencies market is simultaneously the one with the highest share of unexperienced investors and the market which presents more cases of psychological barriers, as well as the observation that Bitcoin is, among all 18 assets, the one presenting stronger evidence of the presence of psychological barriers, may lead us to the conclusion that unexperienced investors are more prone to the behavioral biases which cause psychological barriers than professional traders.

The remainder of this dissertation is organized as follows: Chapter 2 presents our literature review, featuring the above-mentioned categories. Chapter 3 addresses the methodological aspects of our study, namely the data and the various steps of the employed methodology. The fourth chapter shows the empirical results of our work and finally Chapter 5 discusses those results and presents our conclusions.

2 Literature Review

In this section we present a literature review dwelling on brief definitions of ADR, ETF and cryptocurrencies, the relevance and recent evolution of each studied market and the different investor profiles of each of them, market inefficiency and psychological barriers, plausible causes of psychological barriers and previous empirical studies.

2.1 The Markets and Investor Profiles

2.1.1 American Depositary Receipts (ADR) Market

Jayaraman *et al.* (1993) define American Depositary Receipts as negotiable certificates which represent ownership of shares in a company registered in a country other than the USA. The ADR is listed on a stock exchange in the US and is quoted and traded in USD. Bouges *et al.* (2009) add that ADRs enable foreign issuers to enter the US securities market and to meet many commercial, financial and strategic objectives; also, they can use ADRs to gain visibility for their name and products in the United States. For US investors, ADRs provide two major advantages: convenience and cost (Lander, 1995).

ADR programs have been expanding significantly in the past few years. According to the Bank of New York Mellon (2017), 327 new programs were established in the 3-year period between 2014 and 2016 alone, and at the end of 2016 there were a total of 3,492 ADR programs in existence, summing up to a total value of 152.1 billion USD.

2.1.2 Exchange-Traded Funds (ETF) Market

Kosev and Williams (2011) define Exchange-Traded Funds (ETFs) as investment vehicles listed on a stock exchange which provide investors with the return of some benchmark, such as an equity index. Poterba and Shoven (2002) state that the market for ETF shares operates like the market for shares of a common stock: investors can buy or sell ETF shares at any point during the day and ETF share prices may diverge from the underlying net asset value of the securities held in the trust, although this divergence is restricted by the capacity of authorized financial institutions to create and redeem ETF shares.

The appeal of these instruments, which first became available in 1993, is twofold: ETFs offer investors a low-cost mean of gaining a diversified portfolio and the capacity for intraday trading, as well as the ability to invest in a range of asset classes which might be inaccessible to the investor otherwise (Kosev & Williams, 2011).

The referred ability to trade intraday is one of the main features which distinguish ETFs from traditional equity mutual funds, alongside the ability to purchase on margin and sell short and the obligation to purchase through brokerage firms, which entails commission costs. Mutual funds can only be bought or sold at their end-of-day net asset value. Therefore, ETFs and mutual funds may be appropriate for different types of investors: ETFs for investors who demand short-term liquidity and who buy in large lots, equity mutual funds for investors who make many small purchases or sales and who place less value on liquidity (Poterba & Shoven, 2002).

The exchange-traded funds are one of the most attractive financial assets nowadays, being particularly successful in the US stock exchanges, where they are the most actively traded assets among all equity securities. Data from the Investment Company Institute (2018) shows that by June 2018 there were 1,905 ETFs listed in the US ETF market – the largest in the world – for assets worth 3,497.5 billion USD.

2.1.3 Cryptocurrencies Market

Cryptocurrencies are defined by Hayes (2016) as digital monetary and payment systems which exist online via decentralized, distributed networks that employ a share ledger data technology known as *blockchain*. Cryptocurrencies are transferable digital assets, secured by cryptography and created by private individuals, organizations or firms, which means that they are not anyone's liability, unlike government fiat money or any commodity money such as silver or gold coins (White, 2015).

As Trimborn *et al.* (2017) state, the emergence of cryptocurrencies brought not only a new kind of currencies and transaction networks, but also a new kind of investment products which are found to have a low linear dependency with each other, as well as a low linear dependency with traditional assets, which turns them into interesting assets for investors due to the diversification effect; on the other hand, cryptocurrencies are liquidity-constrained.

Although Bitcoin "gets the lion's share of media attention", it is not alone in the free-entry market for cryptocurrencies, as stated by White (2015), who listed more than 500 traded cryptocurrencies. Nonetheless, it remains true that Bitcoin has "a status of quasi-monopoly in the realm of digital currencies by virtue of its first-mover advantage" (Velde, 2013, p.4).

Cryptocurrencies are incontestably one of the financial assets with the most notable growths in the past years. According to HiveEx (2018), in the 4-year period between 2014 and 2017 the number of cryptocurrencies increased from 40 to 1,273, which constitutes a 3,083% increase. The value of exchange trade volume, which equates to the amount of cryptocurrencies traded within a 24-hour period, has also grown exponentially over the past two years. While at the end of 2016 the amount of cryptocurrency traded on major blockchain exchanges was 20.4 million USD, on December 22, 2017 this metric reached an all-time high of 5.4 billion USD, which represents an increase of 26,170.3% over that period.

2.1.4 Investor Profiles

The three financial assets surveyed in our study present significantly different investor profiles. Whilst ADRs and ETFs are mainly traded by institutional investors, cryptocurrencies are traded by a wide range of investors, from experienced institutional investors to *newbie* individuals.

In fact, Yermack (2013) claims that Bitcoin, the first and most popular of cryptocurrencies, appeals to two distinct clienteles: investors who find Bitcoin attractive due to its lack of connection to sovereign government and technology enthusiasts who embrace Bitcoin for online commerce; additionally, Kow (2017) found that the large-crowd, cost effective transactions allowed by cryptocurrencies can drive trades involving "massive numbers of participants".

On the other hand, the ETF primary market – although theoretically open to all investors – aims at fund managers and authorized participants, and the secondary market is usually dominated by institutional investors and authorized participants (Deville, 2008). Likewise, even though the larger ADR listings are actively traded in the NYSE and NASDAQ markets, there is a much significant share of ADR listings which are not traded very actively and are restricted to institutional investors (Karolyi, 2004).

The differences between the profiles of the investors should impact their susceptibility to the behavioral biases which cause psychological barriers; specifically, institutional investors should be less prone to behavioral biases than individual investors, due to their incentives, professionalism and knowledge. In fact, while several previous studies – e.g.

Grinblatt and Titman (1989), Daniel *et al.* (1997) – have provided evidence that some institutions are able to earn superior returns, the evidence from studies regarding the performance of individual investors usually indicates that these are subpar investors, i.e., that their self-managed stock portfolios underperform the market, largely because of trading costs (Barber & Odean, 2013).

In the search of the causes for the individual investors' underperformance, Barber *et al.* (2008) analyze the trading records of Taiwanese investors from 1995 to 1999 and identify four factors which contribute to that phenomenon: perverse stock selection ability, commissions, the transaction tax and poor market timing choices.

Barber and Odean (2013) list three possible behavioral explanations for the poor stock selection ability and overtrading of individual investors: overconfidence, sensation seeking and familiarity. Literature in psychology documents that people generally are overconfident (Moore & Healy, 2008) and that overconfidence can be segmented into overestimation (the belief that one's ability is higher than it actually is), miscalibration (the belief that one knows more than actually does) or better-than-average effect (the belief that one is better than the median person). While the link between miscalibration and trading is weaker, evidence indicates that overestimation and the better-than-average effect are correlated with higher levels of trading by individual investors (Grinblatt & Keloharju, 2009). It is also documented that sensation seeking affects trading and that individual investors tend to overweight geographically or occupationally familiar stocks in their portfolios.

On the other hand, even though institutional investors are not immune to behavioral biases – for instance, the findings of Suto and Toshino (2005) reveal a short-term bias in institutional investors' investment time horizons to improve portfolio performance under pressure either from the customers or from institutional restraints –, there is evidence that they are significantly less susceptible to these biases than individual investors. Shapira and Venezia (2001) compare the behavior of individual and institutional investors in Israel during 1994 and conclude that both exhibit the disposition effect (*i.e*, the tendency to sell winner quicker than losers) but this effect is much stronger for individual investors. Additionally, Lakonishok and Maberly (1990) show that individual investors are much more prone to the weekend effect than institutional investors: there is a tendency for individuals to increase the number of sell relative to buy transactions on Mondays.

Concluding, we expect individual investors to be more prone to the behavioral biases which cause psychological barriers and, subsequently, the cryptocurrencies market – which has a higher preponderance of individual investors – to show a higher frequency of occurrence of psychological barriers than the ADR and ETF markets.

2.2 Market Inefficiency, Psychological Barriers and Price Clustering

Fama (1970) introduced the notion of efficient markets, in which prices always fully reflect available information. That efficiency may be in weak form, if the available information is just historical prices; semi-strong form, if prices also reflect publicly available information; or strong form if private information is also accounted for in prices. This theory, known as the efficient market hypothesis, is one of the most often disputed theories in finance, especially after several studies published in the 1990s proved the existence of market inefficiencies.

In fact, Simon (1955) had already addressed the limitations on knowledge and ability of the "economic man" and the urge to have financial models which rely on limited rationality rather than relatively global rationality.

Arbitrage, defined by Sharpe and Alexander (1990) as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices", could be a way of solving the inefficiencies caused by the investors' limited rationality. However, Shleifer and Vishny (1997) proved the existence of limits to arbitrage (namely fundamental risk, noise trader risk and implementation costs) and therefore the possibility of persisting mispricing in financial markets.

Psychological barriers can also be seen as limits to arbitrage. Mitchell (2001) points out that a psychological barrier can be viewed as an impediment to an individual's mental outlook, that is, an obstacle created by the mind, barring advance or preventing access.

Hirshleifer (2001) found that behavioral biases based on heuristic simplification, self-deception and emotional loss of control persist over time due to the existence of psychological barriers which arise from self-deception and the difficulty of the learning process, therefore hindering the existence of fully rational arbitrageurs.

A clear example of this is the finding of George and Hwang (2004) that the 52-week high price – used as a sort of anchor – explained a large portion of the profits from momentum investing, which challenges the view that markets are efficient in the semi-strong form, since the nearness of a stock's price to its 52-week high is public information. Moreover, Feng and Seasholes (2005) showed that sophistication and trading experience do not eliminate behavioral biases – namely, the disposition effect – even though they do attenuate it. Nonetheless, it is also important to note that Marquering *et al.* (2006) found a tendency of calendar anomalies to disappear after the publication of relevant studies on these anomalies.

Dorfleitner and Klein (2009) summed it up stating that the existence of psychological barriers is not compatible with the efficient market hypothesis – as well as with the assumption of rational investors – as it is connected to the belief in the predictability of stock prices.

2.3 Plausible Causes of Psychological Barriers

2.3.1 Behavioral Biases

Human biases and numbers preferences by individuals have been documented for many years, namely since Yule (1927) studied the frequency of distributions of each final digit 0 to 9 in scale measurement readings by different observers. Kendall and Smith (1938) also dwelled on these preferences, reporting an excessive frequency of even number observations and a human bias against the digits 1, 3 and 9.

Accordingly, Hirshleifer (2001) claims that human fallibility does not shed at the doorstep of the stock exchange, and investors are affected by judgment and decision biases caused by heuristic simplification, self-deception and emotional loss of control. Those biases include anchoring and the representativeness heuristic. Anchoring is defined by Tversky and Kahneman (1974) as the phenomenon that different starting points yield different estimates, since people tend to make estimates by starting from an initial value and then adjust, most of the times insufficiently. By the representativeness heuristic, an event is judged probable to the extent that it represents the essential features of its generating process (Tversky & Kahneman, 1973).

Westerhoff (2003) developed a model in which investors' perception of the fundamental value is anchored to the nearest round number. This model predicts excessive volatility, alternation between period of turbulence and periods of tranquility, and fluctuation of the exchange rate around its perceived fundamental value. Because of anchoring, exchange rates are persistently misaligned, which establishes support and resistance levels in the limits of the fluctuation band. In other words, the perceived fundamental value acts as a psychological barrier.

2.3.2 Aspiration Levels

Sonnemans (2006) indicates that "some investors, when buying a stock, already have an idea for what price they will be able to sell the stock in the future". This notion can be linked to aspiration levels, a concept of psychological theory which was introduced to economic theory by Simon (1955) alongside the notion that the economic agent might not pursue the optimal solution but actually settle for a satisfactory solution.

Additionally, "some financial analysts also use target prices for individual stocks and these are also typically round numbers" (Sonnemans, 2006), which will lead to many limit sell offers being posted at round whole numbers. Cooney *et al.* (2003) brought some empirical evidence into this, as investors submit more limit orders with even-eighth prices than odd-eighth prices on NYSE stocks, thus leading to price clustering on even prices, which is a necessary but not sufficient condition for psychological barriers.

2.3.3 Odd Pricing

"Odd pricing is the tendency of consumers to consider an odd price like 19.95 as significantly lower than the round price of 20.00" (Sonnemans, 2006). This tendency could be originated by the limited amount of memory that people have, which leads them to attach more significance to the first digits of a price, which contain more significant information than the last digits (Brenner & Brenner, 1982).

Odd pricing is very common in consumer goods, with a number of studies – e. g. Holdershaw *et al.* (1997) and Folkertsma (2002) – proving that prices tend to have 9 as the last significant digit. Additionally, Kahn *et al.* (1999) argue that, due to this tendency, "financial institutions would profit by quoting retail loan rates with odd-ending yields (…), but, in contrast, by quoting retail deposit rates with even-ending yields". The theory proposed by the authors predicts that banks tend to set deposit rates at integers and that rates are sticky at those levels. Also, when banks set non-integer rates, those are more likely to be just above, rather than just below integers. The study found empirical evidence of the theory's implications.

2.3.4 Option Exercise Prices

Dorfleitner and Klein (2009) stated that psychological barriers could also be caused by the fact that option exercise prices are usually round numbers. Delta hedgers are frequently most active when the price of the underlying is close to the exercise price – in other words, when the option is at the money – so, purely technical reasons can also cause additional trading activity in the underlying asset.

2.4 Previous Empirical Studies

2.4.1 Stock Indices

The first empirical studies on psychological barriers were performed in the early 1990s and focused mainly on stock indices. Donaldson and Kim (1993) used a sample from 14 October 1974 to 18 May 1990 to test if DJIA's movements around key reference points affected investor sentiment and price behavior, finding that those movements were indeed restrained by support and resistance levels at multiples of 100 but, after breaking through a 100-level, the DJIA moved by more than otherwise warranted. According to the authors, this suggests that some agents are less than fully rational and may be using the absolute price of DJIA to base their trading decisions, but it does not necessarily mean that the market is inefficient. Ley and Varian (1994) also studied the DJIA, with a wider time interval (1 January 1952 to 14 June 1993), and confirmed the non-uniformity of the distribution but added that there is no predictive power on the daily closing prices resulting from psychological barriers.

Koedijk and Stork (1994) tested the existence of psychological barriers in five major stock markets – from Belgium, Germany, Japan, USA and UK – using the daily middle rates (average between bid and ask rates) between 1 January 1980 and 28 February 1992 and using 100-levels as potential barriers. The results from this study underlined the conclusions from the previous studies: psychological barriers are real, but they do not imply predictability of stock returns.

Cyree *et al.* (1999) extended the analysis to six foreign stock indices, alongside the DJIA and the S&P 500, and controlled for the separate and potentially offsetting effects of crossing barriers from below and above using a GJR-in-mean model. Their findings support the existence of psychological barriers and show that these effects are particularly pronounced when the barrier is approached in an upward move.

The study of psychological barriers flew to Asia through the work of Bahng (2003), who used the daily prices of stock indices of seven Asian stock markets from the beginning of 1990 to the end of 1999 to test the existence of barriers at multiples of one hundred, finding that the Taiwanese index is a possible case of market inefficiency, for the frequencies of realized M-values around selected price levels were less frequent than in other price levels. There could also be market inefficiency in the Indonesian index, because of the high frequency of M-values around the selected price levels and low frequencies at mid-range price levels. However, the other five markets do not seem to possess the effect of psychological barriers.

In their turn, Dorfleitner and Klein (2009) focused on European stock indices, namely the German DAZ 30, the French CAC 40, the British FTSE 50 and the Euro-zone related DJ EURO STOXX 50. The data starts in January 1990 for the CAC 40 and the FTSE 50, May 1995 for the DAX 30 and February 1998 for the DJ EURO STOXX 50 and ends in September 2003 for all indices. This study found "fragile traces of psychological barriers" in all indices at the 1000s barrier level and also indications of barriers at the 100s barrier level, expect in the CAC 40. However, the authors did not find any systematic barrier effect for any barrier level, thus concluding that there are no consistent barriers in European stock indices. Another important finding of this study is that some of the barriers found in previous studies seem to have disappeared, which is consistent with the literature findings about disappearing stock market anomalies.

Kalaichelvan and Lim (2012) also tested the existence of psychological barriers in European stock indices, simultaneously testing the appropriateness of the uniform distribution assumption used in a vast majority of the previous studies by comparison with a distribution in line with what is predicted by Benford's Law (Benford, 1938). They found evidence for barriers in one index at the 1000 level but no significant evidence of barriers at the 100 level and 1000 level in the other indices, which is consistent with the findings of Dorfleitner and Klein (2009). With respect to the appropriateness of the uniform distribution, this study found evidence that it is appropriate in most indices at the 100 level but inappropriate in all indices at the 1000 level. Nonetheless, the conclusions drawn from a test that implicitly incorporates the predicted outcomes from Benford's law didn't materially change.

2.4.2 Bonds

The existence of psychological barriers in Bonds was studied for the first time by Burke (2001), who covered the 2-year, 5-year, 10-year and 30-year United States benchmark bonds' yields from 1983 to 2000 and found evidence of yield barriers at integer multiples of 0.25% (e.g., 6.00%, 6.25%, 6.50%, 6.75%) in the 10-year and 30-year benchmark bonds. However, the author also found that barrier effects do not lead to significant predictive power.

2.4.3 Derivatives

The basis for the study of psychological barriers in the derivatives market was provided by Schwartz *et al.* (2004), who tested for price clustering in the open outcry futures markets and found evidence of clustering at prices of x.00 and x.50 for S&P 500 futures contracts, with a higher degree in the daily opening and closing prices, but a lower degree in the settlement prices, using tick-by-tick data in 1999 and 2000.

Chen and Tai (2011) tested for price barriers in Taiwan Futures – specifically, Index Futures, Finance Sector Index Futures and Electronic Sector Futures – from 4 January 2000 to 31 December 2009, reaching the conclusion that prices in round numbers act as barriers with important effects on the conditional mean and variance of the futures price series.

Regarding options, Jang *et al.* (2013) used 15-minute interval historical records of the S&P 500 and the VIX index – the latter is used as a proxy of the former's volatility – from 8 July 2011 to 19 January 2012 to assess the existence of psychological barriers in the prices of stock options. The authors confirmed the presence of price barriers in the S&P 500 prices and they also found evidence of barriers in option pricing, for the VIX Index is not a simple mean-reverting process: it is dependent on the barriers, as it declines relatively by 0.5% when the S&P 500 is close to those levels. Based on these findings, the authors proposed a threshold model which allowed the expected rate of return and volatility to vary if a stock price reached a psychological barrier. That model outperformed the Black-Scholes and the Constant Elasticity of Variance models both in terms of calibration and hedging.

Finally, Dowling *et al.* (2014) tested for psychological barriers around 10$ price levels in Brent and WTI futures, finding that these barriers exist in Brent prices but not in WTI prices. The authors assign this finding to the more prominent role played by Brent as a global benchmark, as well as the greater complexity inherent in Brent fundamental value determination.

2.4.4 Gold and Silver

Aggarwal and Lucey (2007) examined four data sets of gold prices – daily London AM Fix gold prices from 2 January 1980 to 31 December 2000, daily COMEX cash and futures gold from 2 January 1982 to 28 November 2002, high frequency data supplied by UBS London from 28 August 2001 to 9 January 2003 – recurring to a number of statistical procedures, namely uniformity tests, barrier tests and conditional effects tests. The findings of this study indicate that psychological barriers exist in daily gold prices at the 100's digits.

These findings were expanded by Lucey and O'Connor (2016), who also provided the first evidence for silver, using intra-day data from 2 January 1975 to 30 June 2015 for both precious metals. The authors of this study found evidence of clustering away from values ending in 0 and 00, which is a necessary but not sufficient condition for the existence of psychological barriers. Subsequent tests found evidence to support the existence of psychological barriers at numbers ending in 0 and 00 in the price of gold and no evidence that barriers exist for silver.

2.4.5 Single Stocks

Sonnemans (2006) appears to be the first testing the existence of psychological barriers in single stocks, following a number of studies on price clustering of individual stocks. Using data from the Dutch stock market of the period 1990–2001, the author observed round number – 0 and 5 – price barriers during the guilder years (1990-1998) and the euro years (1999-2001) in the original prices, as they find fewer crossings at 0 and 5 than crossings at other whole numbers.

Additionally, Dorfleitner and Klein (2009) examined eight major German stocks - Adidas, BASF, Bayer, Bayerische Hypovereinsbank, Commerzbank, Deutsche Bank, E.ON and Henkel – for indications of psychological barriers at multiples of 1, 10 and 100. They found some evidence of the existence of barriers in the Commerzbank stock at the 10s and 100s levels, in the Henkel stock at the 10s level and weak evidence in Adidas at the 10s and 100s levels, HVB at the 10s and 100s levels and EON at the 10s level. However, the authors did not find any systematic barrier effect for any barrier level, thus, the main result of this study is that there are no consistent barriers in German stocks.

Chen (2014) looked for international evidence of price clustering and price barriers using a data set consisting of 35 328 stocks traded on 68 countries from 1 January 2000 to 31 December 2009. This study found a higher propensity for prices to cluster and resist on last digit 0; this phenomenon is stronger in countries with timely disclosure and effective dissemination of information, i.e., more transparent countries.

In a more recent study, Lobão and Fernandes (2018) found no consistent psychological barriers in individual stock prices near round numbers in the markets of Taiwan, Brazil and South Africa.

3 Methodological Aspects

In this chapter we present the methodological aspects of our study, namely the data and methodology used, with an analysis of our data sample and its main features and a thorough explanation of each of the tests which compose our methodology.

3.1 Data

The main objective of our study is to examine if the markets of American Depositary Receipts, Exchange-Traded Funds and Cryptocurrencies present significant signs of the existence of psychological barriers. For that purpose, we selected six of the most liquid assets from each market, hand-picked with the concern of providing a diversified sample, and collected the daily closing quotes for each asset for the period between January 1, 2008 and December 31, 2017.

Therefore, the selected American Depositary Receipts (ADRs) were Alibaba 1:1, Nokia 1:10, Novartis 1:1, Royal Dutch Shell 1:2, Vale On 1:1 and Teva Pharmaceuticals 1:1; the selected Exchange-Traded Funds (ETFs) were iShares MSCI Brazil, Horizons Capital Dax Germany, iShares MSCI Japan, iShares MSCI South Africa, iShares Russell 1000 and SPDR S&P 500; the selected cryptocurrencies were Bitcoin, Dash, Ethereum, Litecoin, NEM and Ripple.

For some assets – namely the Alibaba ADR, the Germany ETF and all cryptocurrencies – the first trading day was after January 1, 2008; for those assets the start date of our sample corresponds to the first trading day of the asset. The data for ADRs and ETFs was collected from Thomson Reuters Datastream, while the data for cryptocurrencies was retrieved from CoinMarketCap.

Table 1 presents the summary of the information above mentioned, with the denomination which will be used from now on for each asset, as well as the summary statistics of the data used in our study.

Table 1 – Data used in our study

Market	Asset	Start Date	End Date	N	Return Series				Level Series	
					Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
ADR	Alibaba	Sep 19, 2014	Dec 31, 2017	856	0.0711	1.9133	0.2348	3.7718	57.39	191.19
	Nokia	Jan 1, 2008		2609	-0.0809	2.9127	-0.3293	9.5049	1.69	38.39
	Novartis			2609	0.0167	1.2673	-0.0999	5.2864	33.96	106.12
	Shell			2609	-0.0075	1.8483	-0.0199	9.2449	36.96	87.92
	Teva			2609	-0.0344	1.9461	-1.6565	30.6603	11.23	72.00
	Vale			2609	-0.0377	3.3276	-0.1251	6.1480	2.15	43.91
ETF	Brazil	Jan 1, 2008		2609	-0.0265	2.4367	-0.3770	10.6983	17.33	100.47
	Germany	Oct 23, 2014		832	0.0270	1.1844	-0.8977	9.5630	21.46	31.91
	Japan	Jan 1, 2008		2609	0.0046	1.4031	0.2532	13.4178	27.48	60.62
	South Africa			2609	0.0028	2.2778	-0.2685	11.2820	25.87	76.87
	US:Russell 1000			2609	0.0239	1.2423	-0.3469	10.4627	37.06	149.93
	US:S&P 500			2609	0.0231	1.2601	-0.0879	14.9512	68.11	268.20
Cryptocurrencies	Bitcoin	Apr 28, 2013		1709	0.2727	4.4018	-0.1384	8.9278	68.43	19 497.40
	Dash	Feb 14, 2014		1417	0.5608	8.5917	3.1572	41.6881	0.31	1550.85
	Ethereum	Aug 7, 2015		878	0.6397	8.5247	-3.7296	64.9273	0.43	826.82
	Litecoin	Apr 28, 2013		1709	0.2328	6.9101	1.8842	26.9030	1.16	358.34
	NEM	Apr 1, 2015		1006	0.8315	9.3127	2.0248	16.8800	0.00	1.06
	Ripple	Aug 4, 2013		1611	0.3707	7.9535	2.2587	29.2155	0.00	2.30

This table shows us that all the studied cryptocurrencies have provided positive and significant mean returns in the period under analysis, while ADRs and ETFs provided mean returns much close to zero. The standard deviation of the return series and the minimum and maximum of the level series indicate us that cryptocurrencies are also clearly more volatile than the other two types of financial assets.

3.2 Methodology

The methodology of our study uses as a clear guideline the methodology followed in the work of Aggarwal and Lucey (2007), for this was the first study which used the three main tests on psychological barriers and that methodology can also be used on the markets targeted by our study. This methodology consists of a uniformity test, a barrier hump test, a barrier proximity test and a conditional effects test.

The uniformity test was introduced by Ley and Varian (1994). To perform this test, we will regress the daily values of each asset and then perform a Kolmogorov-Smirnov Z statistic test for uniformity.

The barrier – proximity and hump – tests were first used by Burke (2001). In the barrier proximity test, we will test the frequency of occurrence of M-values near the M-value of the psychological barrier; in the barrier hump test, we will regress the M-values frequency to a quadratic equation, with the intent of testing if the distribution of the M-values follows a hump distribution, as predicted by Donaldson and Kim (1993).

Additionally we use a conditional effects test, based on the test introduced by Cyree *et al.* (1999), in order to assess if approaching a barrier on a downward or upward movement has a different impact, by regressing their values in a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) type model using dummy variables for periods in the neighborhood of crossing the barrier as explanatory variables of the return of each asset and performing a Wald test on the difference between the variables for the upward and the downward movement. Simultaneously, we will also be testing if variance is homogeneous and, if it is not, testing for differences in variance to the various approaches of barriers.

3.2.1 Definition of Barriers

Following Brock *et al.* (1992), we will use the so-called band technique and define barriers as an interval between two numbers at the same distance from the number which constitutes the actual barrier. The main reason to justify this technique is the idea that market players will become more active at a certain level before the price touches a round number. Dorfleitner and Klein (2009) defined the barrier level l as the number of zeros that a barrier has; we will follow the same definition, but we will also need to introduce the barrier levels $l = -1$ and $l = -2$ for the 0.1-level and 0.01-level barriers, respectively, which will be used for the tests on some of the selected cryptocurrencies. We define as potential barriers the multiples of 0.01, 0.1, 1, 10, 100 and 1000 and define intervals with an absolute length of 2%, 5% and 10% to the corresponding barriers, thus considering the following restriction bands:

- Barrier level $l = 3$ (1000s): 980-1020; 950-1050; 900-1100.
- Barrier level $l = 2$ (100s): 98-102; 95-105; 90-110.
- Barrier level $l = 1$ (10s): 9.8-10.2; 9.5-10.5; 9.0-11.0.
- Barrier level $l = 0$ (1s): 0.98-1.02; 0.95-1.05; 0.90-1.10.
- Barrier level $l = -1$ (0.1s): 0.098-0.102; 0.095-0.105; 0.090-0.110.
- Barrier level $l = -2$ (0.01s): 0.0098-0.0102; 0.0095-0.0105; 0.0090-0.0110.

For each financial asset, we then check the barrier levels which are susceptible of constituting psychological barriers and examine each of them. For the majority of ADRs and ETFs, more stable than cryptocurrencies, we will examine only two barrier levels. In the case of cryptocurrencies, due to the galloping growth of their daily quotes in the sample years, we feel the need to test 3, 4 or even 5 potential barriers for each asset.

3.2.2 M-values

The concept of M-values was introduced by Donaldson and Kim (1993), who considered potential barriers at the levels …, 300, 400, …, 3400, 3500, …, i.e. at:

$$k\ X\ 100, k = 1, 2, \ldots \tag{1.1}$$

Five years later, De Ceuster *et al.* (1998) found two problems with this approach: not only it was too narrow, as the series was not multiplicatively regenerative, leading to 3400 being considered a barrier while 340 was not, for instance, but also the gap between barriers, as defined by Eq. (1.1), would tend to zero as the price series increased, intuitively reducing the probability of those levels to represent psychological barriers. Thus, the authors claim we should consider the possibility of barriers at the levels …, 10, 20, …, 100, 200, …, 1000, 2000, …, i.e. generally at:

$$k\ X\ 10^l, k = 1, 2, \ldots, 9; l = \ldots, -1, 0, 1, \ldots \tag{1.2}$$

and also at the levels …, 10, 11, …, 100, 110, …, 1000, 1100, …, i.e. generally at:

$$k\ X\ 10^l, k = 10, 11, \ldots, 99; l = \ldots, -1, 0, 1, \ldots \tag{1.3}$$

The M-values which we will use in our study can now be defined according to these barriers.

$$M_k = \left[P_t * \frac{100}{k}\right] mod\ 100, \qquad k = 0.01, 0.1, 1, 10, 100, 1000 \tag{1.4}$$

where $\left[P_t * \frac{100}{k}\right]$ is the integer part of $P_t * \frac{100}{k}$ and $mod\ 100$ is the reduction modulo of 100.

Illustrating this with a purely theoretical quote of 1234.56789, the M0.01 is 78, the M0.1 is 67, the M1 is 56, the M10 is 45, the M100 is 34 and the M1000 is 23.

3.2.3 Uniformity Test

After defining the M-values, the next step is to examine if they follow a uniform distribution, through the uniformity test introduced by Ley and Varian (1994), which consists of a Kolmogorov-Smirnov Z-statistic test where we will be testing H0: uniform distribution against H1: non-uniform distribution.

In the presence of psychological barriers, it is expected to reject the null hypothesis. However, it is important to underline that this rejection does not by itself confirm the existence of such barriers. Additionally, De Ceuster *et al.* (1998) stated that, as the series grows, the interval between barriers widens and, as a result, the distribution of digits and their frequency of occurrence tends to stop being uniform.

3.2.4 Barrier Tests

Afterwards, we will perform two barrier tests, which were first mentioned by Donaldson and Kim (1993) and then explored by Burke (2001) and Aggarwal and Lucey (2007) in their studies on the US bond yields and gold prices, respectively. The intent of these tests is to assess if the series observations on or near a barrier occur less frequently than what would be predicted by a uniform distribution, examining the shape of the M-values distribution. We proceed to the explanation of each test.

3.2.4.1 Barrier Proximity Test

This test examines the frequency of M-values in the proximity of potential barriers, applying the following equation:

$$f(M) = \alpha + \beta D + \varepsilon, \qquad M = 00,01,\dots,99 \tag{2.1}$$

where $f(M)$ is defined as the frequency with which a quote closes with its last two digits in cell M, minus 1 percentage point, and D is a dummy variable which takes the value 1 if the price of the asset is at the potential barrier and 0 elsewhere. Besides the strict dummy, which takes the value 1 if M=00 and takes the value 0 otherwise, we will study 3 dummies for each potential barrier level:

- D_{98-02} = 1 if M ≥ 98 or M ≤ 02, = 0 otherwise;
- D_{95-05} = 1 if M ≥ 95 or M ≤ 05, = 0 otherwise;
- D_{90-10} = 1 if M ≥ 90 or M ≤ 10, = 0 otherwise;

The results of this test are based in the β coefficients, which are expected to be negative and statistically significant in the presence of psychological barriers.

3.2.4.2 Barrier Hump Test

The second barrier test examines the entire shape of the distribution of M-values and is broader than the barrier proximity test as it does not focus solely on the proximity of the potential barriers. We will implement this test using the following equation, which was introduced by Bertola and Caballero (1992):

$$f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon, \qquad M = 00,01,\ldots,99 \tag{2.2}$$

where $f(M)$ is once again defined as the frequency with which a quote closed with its last two digits in cell M, minus 1 percentage point, and the independent variables are the M-value and its square.

In the presence of psychological barriers, the M-values are expected to follow a hump-shape distribution, which will be reflected in Eq. (2.2) through negative and statistically significant δ, whereas under the null hypothesis of no barriers, δ should be zero and the M-values should follow a uniform distribution.

3.2.5 Conditional Effects Test

The final test of our methodology was introduced by Cyree *et al.* (1999) with the intent of detecting changes in the conditional mean and variance of the distribution of returns during the sub-periods before and after crossing a barrier, either from above or below. The above-mentioned authors use a 10-day window before and after crossing a barrier, while Aggarwal and Lucey (2007) perform a 5-day analysis. Once again, we choose to follow the methodology of Aggarwal and Lucey (2007), which has been used in the majority of studies on psychological barriers in recent years, as 10 days has been considered too big of a range to study the impact of barriers.

In order to identify if a barrier is crossed in an upward or downward movement and examine the difference in returns between the 5-day periods before and after the barrier is crossed, we will use four dummy variables: UB for the 5-day period before prices cross a barrier on an upward movement, UA for the 5-day period after prices cross a barrier on an upward movement, DB for the 5-day period before prices cross a barrier on a downward movement and DA for the 5-day period after prices cross a barrier on a downward movement. Each of these dummies will take the value 1 on the identified days and the value 0 elsewhere. Acknowledging, as stated by Cyree *et al.* (1999), that the distributional shifts implied by psychological barriers invalidate basic assumptions of OLS, we will then regress the following equations using a GARCH (1,1) model:

$$R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t \tag{3.1}$$

$$\varepsilon_t \sim N(0, V_t) \quad (3.2)$$

$$V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t \quad (3.3)$$

In the absence of barriers, it is expected that the coefficients of the indicator variables take the value zero both in the mean and variance equations, whereas any coefficient significantly different from zero (either positive or negative) might indicate the presence of psychological barriers.

We will then perform a Wald test on the difference between the coefficients of two dummy variables, to examine if there are significant differences in return and/or variance from crossing a barrier on an upward or downward movement.

Following Cyree *et al.* (1999) and Aggarwal and Lucey (2007), the four null hypotheses to be tested are:

H1: There is no significant difference in the conditional mean return before and after an upwards crossing of a barrier;

H2: There is no significant difference in the conditional mean return before and after a downwards crossing of a barrier;

H3: There is no significant difference in the conditional variance before and after an upwards crossing of a barrier;

H4: There is no significant difference in the conditional variance before and after a downwards crossing of a barrier.

4 Empirical Study

In this section, we present the results of the uniformity, barrier proximity, barrier hump and conditional effects test, as well as an analysis to each of those tests' results, regarding not only a global analysis to the whole sample but also a comparison between the 3 sub-samples of our study: ADRs, ETFs and cryptocurrencies, composed of 6 assets each.

4.1 Uniformity Test

Table 2 shows the results of the uniformity tests for each financial asset, using a Kolmogorov-Smirnov Z-test which studies the distribution of the M-values for a total of 18 financial assets and 50 potential barriers. Overall, the studied financial assets show signs of psychological barriers, as there is statistically significant evidence at a 5 percent significance level that M-values do not follow a uniform distribution at, at least, one barrier level for all the 18 assets and at, at least, two barrier levels for 14 of the 18 assets under study (the exceptions are the Shell and Vale ADRs and the Germany and South Africa ETFs).

The Nokia and Teva ADRs, the Brazil, Japan and Russel 1000 ETFs, and the Ethereum, Litecoin, NEM and Ripple cryptocurrencies reject uniformity at a 5 percent significance level for every potential barrier level. The results of this test do not show any significant differences between the three types of financial assets under study.

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Table 2 – Uniformity test results

			M0.01	M0.1	M1	M10	M100	M1000
ADR	Alibaba	Kolmogorov (D) - Stat. Value (adjusted)	--	--	2.640853	0.916470	10.43078	--
		P-value	--	--	0.0000***	0.3704	0.0000***	--
	Nokia	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.962082	9.355578	--	--
		P-value	--	--	0.0009***	0.0000***	--	--
	Novartis	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.205620	2.498224	18.51664	--
		P-value	--	--	0.1093	0.0000***	0.0000***	--
	Shell	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.948468	1.264737	--	--
		P-value	--	--	0.0010***	0.0816*	--	--
	Teva	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.822424	1.809143	--	--
		P-value	--	--	0.0026***	0.0029***	--	--
	Vale	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.295465	4.072440	--	--
		P-value	--	--	0.0697*	0.0000***	--	--
ETF	Brazil	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.659428	2.532433	--	--
		P-value	--	--	0.0081***	0.0000***	--	--
	Germany	Kolmogorov (D) - Stat. Value (adjusted)	--	--	0.827227	4.759643	--	--
		P-value	--	--	0.5005	0.0000***	--	--
	Japan	Kolmogorov (D) - Stat. Value (adjusted)	--	--	3.402057	6.867324	--	--
		P-value	--	--	0.0000***	0.0000***	--	--
	South Africa	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.292552	2.480497	--	--
		P-value	--	--	0.0708*	0.0000***	--	--
	US:Russell 1000	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.625609	1.629835	5.100530	--
		P-value	--	--	0.0101**	0.0099***	0.0000***	--
	US:S&P 500	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.150749	3.205473	10.35219	--
		P-value	--	--	0.1415	0.0000***	0.0000***	--
Cryptocurrencies	Bitcoin	Kolmogorov (D) - Stat. Value (adjusted)	--	--	1.900118	1.095154	3.199988	6.327789
		P-value	--	--	0.0015***	0.1815	0.0000***	0.0000***
	Dash	Kolmogorov (D) - Stat. Value (adjusted)	--	0.111838	0.026889	0.172266	0.186074	0.264230
		P-value	--	0.0000***	0.2538	0.0000***	0.0000***	0.0000***
	Ethereum	Kolmogorov (D) - Stat. Value (adjusted)	--	5.269663	2.057020	3.405512	7.523218	--
		P-value	--	0.0000***	0.0004***	0.0000***	0.0000***	--
	Litecoin	Kolmogorov (D) - Stat. Value (adjusted)	--	--	3.569276	14.03169	15.61957	--
		P-value	--	--	0.0000***	0.0000***	0.0000***	--
	NEM	Kolmogorov (D) - Stat. Value (adjusted)	8.549875	13.32748	17.56190	--	--	--
		P-value	0.0000***	0.0000***	0.0000***	--	--	--
	Ripple	Kolmogorov (D) - Stat. Value (adjusted)	0.215958	0.631059	0.810789	--	--	--
		P-value	0.0000***	0.0000***	0.0000***	--	--	--

Table 2 presents the results of a Kolmogorov-Smirnov test for uniformity. The first line for each asset shows the value of the t-statistic; p-value shows the marginal significance of this statistic. H0: uniformity; H1: non-uniformity. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

4.2 Barrier Tests

4.2.1 Barrier Proximity Test

The following tables 3 to 14 show the results of the barrier proximity tests performed on the selected American Depositary Receipts (tables 3-6), Exchange-Traded Funds (tables 7-10) and Cryptocurrencies (tables 11-14). As previously mentioned in Section 3.2.4.1, in the presence of a psychological barrier it is expected that β is negative and significant, which means that there is a lower frequency on the M-values which constitute the potential barrier.

Focusing on the American Depositary Receipts, if we consider a barrier in the exact zero modulo point, we see in Table 3 that none of the selected assets present negative and significant estimates for β for any barrier level; we find some negative β estimates, namely for Alibaba, Nokia and Novartis, but all of them have p-values over 10% and thus do not significantly reject uniformity. If we assume a barrier in the 98-02 interval (Table 4), the findings are almost the same of the strict barrier test, the only exception being Nokia, which presents a negative estimate for β, now significant at a 10 percent significance level, for the 10-level barrier. Assuming a barrier in the 95-05 interval (Table 5), once again the only negative and significant estimate for β we can find is the one of Nokia for the 10-level barrier, which is now significant at a 1 percent level. Finally, for the 90-10 interval barrier (Table 6), we find negative and significant β estimates for Nokia at the 10-level barrier – significant at a 1 percent level –, for Novartis at the 10 and 100-level potential barriers – both significant at a 5 percent level – and for Vale at the 10-level barrier – significant at a 1 percent level. Curiously, as we widen the barrier intervals, we find changes in the signal of the β estimates for Nokia and Novartis at the 1-level barrier, as well as for Shell and Vale at the 10-level, the latter of which actually becomes significant at a 1 percent level for the 90-10 interval barrier, as previously mentioned. Summing up, we do not reject the no-barrier hypothesis for Alibaba, Shell and Teva at any potential barrier level, whereas we find some signs of the existence of psychological barriers for Nokia around the 10-level round numbers, Novartis around the 10-level and 100-level round numbers and Vale around the 10-level round numbers.

As for the Exchange-Traded Funds, we see in Table 7 that none of them have negative and significant β estimates for any barrier level if we consider a barrier in the exact zero modulo point; all the assets except Japan and S&P 500 present negative estimates for β but too close to zero to support the theory of lower frequency of M-values at barrier points. Assuming a 98-02 interval barrier (Table 8), the Germany ETF is the only one which seems to reject the no-barrier hypothesis, for the 10-level barrier, with a negative estimate for β which is significant at 1 percent significance level. Widening the interval to 95-05 (Table 9), we find negative and significant β estimates for Brazil and Germany, both at the 10-level barrier, statistically significant at 10 percent and 1 percent level, respectively. Finally, assuming a barrier in the 90-10 interval (Table 10), we find three negative and significant β estimates: Brazil at the 10-level barrier, significant at a 5 percent level; Germany at the 10-level barrier, significant at a 1 percent level; and Russell 1000 at the 100-level barrier, significant at a 10 percent level. This time, widening the barrier interval caused only one estimate to change signal, namely the estimate for Japan at the 1-level barrier; and even though this estimate became negative for the 90-10 barrier interval, it is still not significant at any of the confidence levels used in our study. Summing up, we do not reject the no-barrier hypothesis for Japan, South Africa and S&P 500 for any potential barrier level; on the other hand, we find some signs of the existence of psychological barriers for Brazil and Germany around the 10-level round numbers and Russell 1000 around the 100-level round numbers.

Testing for psychological barriers in cryptocurrencies, although the methodology is exactly the same, there is a significant difference in the number of potential barriers tested, which is explained by the much higher range of the daily quotes of these assets compared to ADR's and ETF's (see Table 1): while we tested for a total of 14 potential barrier levels on the 6 selected ADRs and also 14 potential barrier levels on the 6 selected ETFs, we must test for a total of 22 potential barrier levels on the 6 selected cryptocurrencies. That being said, just like what happened with both ADRs and ETFs, when we consider a barrier to be in the exact zero modulo point (Table 11), we find no negative and significant β estimates for any asset or any barrier level, even though we find negative (but not significant) estimates for all assets except NEM. When we assume a barrier in the 98-02 interval (Table 12), Bitcoin and Dash present negative estimates for β for the 1000-level potential barrier, both significant at a 10 percent level. Widening the interval to 95-05 (Table 13), we find 9 negative and significant β estimates: Bitcoin at the 100 and 1000-level barriers, Dash at the 1, 10, 100 and 1000-level barriers, Litecoin at the 10 and 100-level barriers and Ripple at the 0.01-level barrier. Finally, considering a barrier to be in the 90-10 interval, we find the same negative and significant estimates for β of the previous table except for Dash at the 1-level barrier, leading to a total of 8 negative and significant β estimates. Once again, as we widen the barrier intervals some estimates change signal, but unlike what happened with ADRs and ETFs, where we found exclusively estimates which were positive for the shorter intervals and negative for the larger ones, with cryptocurrencies we also find some estimates which become positive with the enlargement of the intervals, namely for Ethereum at the 10 and 100-level barriers, Litecoin at the 1-level barrier and Ripple at the 0.1-level barrier. Summing up, we do not reject the no-barrier hypothesis for Ethereum and NEM at any potential barrier level; Bitcoin presents some signs of the existence of a psychological barrier around the 100 and 1000-level round numbers; Dash presents some signs of the existence of a psychological barrier around the 1, 10, 100 and 1000-level round numbers; Litecoin presents some signs of the existence of a psychological barrier around the 10 and 100-level round numbers and the same happens with Ripple at the 0.01-level round numbers.

Overall, the R-squared values are low, which is in line with previous studies like Bahng (2003). In the field of Behavioral Finance, it is very common to find low R-squared values, as we are analyzing human psychological behavior.

4.2.2 Barrier Hump Test

Following the barrier proximity test, we now examine the entire shape of the distribution of M-values. As explained in Section 3.2.4, in the presence of barriers these values are assumed to follow a hump-shape distribution, and thus δ is expected to be negative and significant in the presence of such barriers. Tables 15, 16 and 17 show the results of these tests on the selected American Depositary Receipts, Exchange-Traded Funds and Cryptocurrencies, respectively, which seem to corroborate most of the results obtained from the barrier proximity test.

In the case of the ADRs, we find evidence of a hump-shape distribution of M-values for Nokia, Novartis and Vale at the 10-level barrier, as well as for Novartis at the 100-level barrier, which are precisely the same four potential barriers which presented negative and significant β estimates – therefore showing signs of the existence of psychological barriers – in the barrier proximity test. We find only one other estimate which is negative but not significant at any confidence level: Alibaba at the 10-level barrier; all the other δ estimates are positive.

As for the Exchange-Traded Funds, we only find evidence that M-values follow a hump-shape distribution for Brazil and Germany, both at the 10-level barrier. Therefore, from the trio of potential barriers which presented signs of the existence of psychological barriers around round numbers we drop the Russell 1000 at the 100-level barrier, which actually presents a negative estimate but with a p-value higher than all the confidence levels used in our study, just like Japan and South Africa at the 1-level barrier and Russell 1000 at the 10-level barrier.

At last, with respect to cryptocurrencies, we find negative and significant δ estimates for Bitcoin at the 100 and 1000-level, Dash at the 10-level, Litecoin at the 10 and 100-level and Ripple at the 0.01-level, leading to a total of 6 potential barriers, which means we drop 3 of the 9 barrier levels which presented some signs of the existence of psychological barriers in the proximity test – namely Dash at the 1, 100 and 1000-level – and corroborate the absence of psychological barriers for Ethereum and NEM. The three *dropped* potential barriers for Dash presented negative but insignificant estimates for δ, as well as Bitcoin at the 1 and 10-level barriers.

Summing up, at this point of our battery of tests, we have found consistent signs of the existence of psychological barriers around round numbers for 3 of the 6 selected American Depositary Receipts – Nokia, Novartis and Vale –, as well as for 2 of the 6 selected Exchange-Traded Funds – Brazil and Germany – and for 4 of the 6 selected cryptocurrencies – Bitcoin, Dash, Litecoin and Ripple. We also observe that, as we widen the barrier intervals, the existence of evidence supporting psychological barriers tends to become more frequent and also more significant.

Table 3 – Barrier proximity test results for the strict dummy – ADR

ADR	Strict dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Alibaba	2.647975	0.0000***	0.383405	-0.184084	0.6267	0.002423	0.287926	0.7885	0.000738
Nokia	0.073948	0.7611	0.000947	-0.390645	0.5317	0.004005	--	--	--
Novartis	0.190096	0.3544	0.008759	-0.080916	0.7601	0.000956	-0.468077	0.6683	0.001881
Shell	0.654688	0.0023***	0.090767	0.228812	0.2976	0.011066	--	--	--
Teva	0.886984	0.0002***	0.129367	0.770836	0.0020***	0.093638	--	--	--
Vale	0.112664	0.5408	0.003829	0.267528	0.3547	0.008747	--	--	--

Table 3 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M=00 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 4 – Barrier proximity test results for the 98-02 dummy – ADR

ADR	98-02 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Alibaba	0.472209	0.0153**	0.058500	-0.093458	0.5886	0.002996	0.349238	0.4755	0.005210
Nokia	0.028646	0.7965	0.000682	-0.503924	0.0751*	0.031972	--	--	--
Novartis	-0.068185	0.4672	0.005407	0.077061	0.5237	0.004161	-0.277985	0.5772	0.003183
Shell	0.085130	0.3959	0.007364	0.036715	0.7150	0.001367	--	--	--
Teva	0.351415	0.0016***	0.097430	0.432107	0.0001***	0.141178	--	--	--
Vale	0.117407	0.1610	0.019949	-0.019770	0.8812	0.000229	--	--	--

Table 4 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥98 or M≤02 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 5 – Barrier proximity test results for the 95-05 dummy – ADR

ADR	95-05 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Alibaba	0.212882	0.1199	0.024505	-0.049641	0.6801	0.001742	0.582800	0.0854*	0.029901
Nokia	0.027445	0.7227	0.001290	-0.634208	0.0010***	0.104375	--	--	--
Novartis	-0.023451	0.7199	0.001318	-0.023451	0.7807	0.000794	-0.367981	0.2884	0.011495
Shell	0.035275	0.6140	0.002606	0.003954	0.9550	0.000033	--	--	--
Teva	0.195794	0.0122**	0.062336	0.403295	0.0000***	0.253466	--	--	--
Vale	0.066596	0.2545	0.013228	-0.148735	0.1041	0.026735	--	--	--

Table 5 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥95 or M≤05 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 6 – Barrier proximity test results for the 90-10 dummy – ADR

ADR	90-10 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Alibaba	0.184775	0.0783*	0.031284	-0.019435	0.8336	0.000453	0.424194	0.1033	0.026843
Nokia	-0.004367	0.9414	0.000055	-0.759854	0.0000***	0.253897	--	--	--
Novartis	-0.050574	0.3129	0.010389	-0.131436	0.0401**	0.042280	-0.528818	0.0454**	0.040230
Shell	0.014116	0.7928	0.000707	-0.011298	0.8337	0.000452	--	--	--
Teva	0.127324	0.0348**	0.044671	0.328325	0.0000***	0.284673	--	--	--
Vale	0.044151	0.3258	0.009853	-0.186885	0.0071***	0.071526	--	--	--

Table 6 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥90 or M≤10 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 7 – Barrier proximity test results for the strict dummy – ETF

ETF	Strict dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Brazil	0.306244	0.1440	0.021657	-0.042200	0.8589	0.000324	--	--	--
Germany	-0.160256	0.7100	0.001417	-0.767288	0.2279	0.014802	--	--	--
Japan	2.396909	0.0891*	0.029207	0.228812	0.5432	0.003784	--	--	--
South Africa	-0.003484	0.9853	0.000003	-0.197065	0.3305	0.009663	--	--	--
US: Russell 1000	-0.003484	0.9852	0.000004	-0.274497	0.1403	0.022055	-0.235781	0.7345	0.001179
US: S&P 500	0.073948	0.6800	0.001743	0.306244	0.1506	0.020968	0.306244	0.6148	0.002594

Table 7 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M=00 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 8 – Barrier proximity test results for the 98-02 dummy – ETF

ETF	98-02 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Brazil	0.020577	0.8306	0.000469	-0.132739	0.2188	0.015388	--	--	--
Germany	0.187247	0.3403	0.009284	-0.875506	0.0021***	0.092464	--	--	--
Japan	-0.084323	0.8965	0.000173	0.496661	0.0031***	0.085536	--	--	--
South Africa	0.012507	0.8852	0.000214	0.028646	0.7572	0.000980	--	--	--
US: Russell 1000	0.068992	0.4209	0.006622	-0.108531	0.2022	0.016543	-0.366747	0.2464	0.013688
US: S&P 500	0.060923	0.4563	0.005676	0.004438	0.9638	0.000021	-0.019770	0.9433	0.000052

Table 8 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥98 or M≤02 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 9 – Barrier proximity test results for the 95-05 dummy – ETF

ETF	95-05 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Brazil	0.058766	0.3796	0.007886	-0.133074	0.0755*	0.031876	--	--	--
Germany	0.153218	0.2622	0.012812	-0.816669	0.0000***	0.165819	--	--	--
Japan	0.039190	0.9309	0.000077	0.352398	0.0026***	0.088754	--	--	--
South Africa	-0.050857	0.3983	0.007290	0.039190	0.5435	0.003779	--	--	--
US: Russell 1000	0.050935	0.3935	0.007439	-0.007791	0.8959	0.000176	-0.348405	0.1128	0.025461
US: S&P 500	0.078341	0.1676	0.019345	0.043105	0.5264	0.004108	0.097917	0.6128	0.002623

Table 9 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥95 or M≤05 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 10 – Barrier proximity test results for the 90-10 dummy – ETF

ETF	90-10 dummy								
	M1			M10			M100		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Brazil	0.051082	0.3199	0.010098	-0.145298	0.0108**	0.064396	--	--	--
Germany	0.074477	0.4789	0.005130	-0.577561	0.0001***	0.140540	--	--	--
Japan	-0.078298	0.8214	0.000522	0.249773	0.0056***	0.075557	--	--	--
South Africa	-0.011298	0.8073	0.000610	0.067255	0.1730	0.018861	--	--	--
US: Russell 1000	0.007185	0.8757	0.000251	0.016427	0.7193	0.001324	-0.288541	0.0870*	0.029593
US: S&P 500	0.021047	0.6308	0.002366	0.039530	0.4493	0.005854	0.485430	0.0008***	0.109236

Table 10 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥90 or M≤10 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 11 – Barrier proximity test results for the strict dummy – Cryptocurrencies

	Strict dummy																	
Cryptocurrency	M0.01			M0.1			M1			M10			M100			M1000		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Bitcoin	--	--	--	--	--	--	0.822148	0.0017***	0.096268	-0.123529	0.6000	0.002817	-0.182634	0.5887	0.002995	-0.655472	0.4233	0.006554
Dash	--	--	--	8.542019	0.0030***	0.086170	-0.154687	0.5953	0.002890	-0.368541	0.6301	0.002375	-0.653679	0.4320	0.006313	-0.938817	0.3446	0.009120
Ethereum	--	--	--	1.981086	0.0000***	0.263860	0.025310	0.9440	0.000051	-0.089736	0.8709	0.000271	-0.664964	0.6899	0.001631	--	--	--
Litecoin	--	--	--	--	--	--	-0.478158	0.1363	0.022500	-0.891891	0.4467	0.005920	-0.891891	0.4781	0.005148	--	--	--
NEM	2.303352	0.3506	0.008895	33.22891	0.0000***	0.828524	69.37567	0.0000***	0.991824	--	--	--	--	--	--	--	--	--
Ripple	-0.006897	0.9926	0.000001	-0.696600	0.8064	0.000616	64.95056	0.0000***	0.959645	--	--	--	--	--	--	--	--	--

Table 11 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M=00 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 12 – Barrier proximity test results for the 98-02 dummy – Cryptocurrencies

	98-02 dummy																	
Cryptocurrency	M0.01			M0.1			M1			M10			M100			M1000		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Bitcoin	--	--	--	--	--	--	0.327061	0.0065***	0.073097	-0.045464	0.4290	0.006395	-0.165686	0.2815	0.011827	-0.658434	0.0762*	0.031732
Dash	--	--	--	0.938231	0.4850	0.004988	-0.116629	0.3798	0.007881	-0.502916	0.1481	0.021223	-0.517773	0.1714	0.019005	-0.800059	0.0760*	0.031780
Ethereum	--	--	--	0.553890	0.0014***	0.098963	0.002398	0.9884	0.000002	0.218199	0.3858	0.007683	-0.117492	0.8773	0.000244	--	--	--
Litecoin	--	--	--	--	--	--	-0.128730	0.3815	0.007825	-0.670752	0.2089	0.016066	-0.855533	0.1344	0.022727	--	--	--
NEM	5.413833	0.0000***	0.235764	8.615674	0.0000***	0.267245	14.70545	0.0000***	0.213814	--	--	--	--	--	--	--	--	--
Ripple	-0.451501	0.1820	0.018103	-0.817407	0.5283	0.004069	16.22333	0.0000***	0.287265	--	--	--	--	--	--	--	--	--

Table 12 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥98 or M≤02 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 13 – Barrier proximity test results for the 95-05 dummy – Cryptocurrencies

	95-05 dummy																	
Cryptocurrency	M0.01			M0.1			M1			M10			M100			M1000		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Bitcoin	--	--	--	--	--	--	0.119598	0.1589	0.020145	-0.071663	0.3379	0.009376	-0.227062	0.0326**	0.045780	-0.681306	0.0078***	0.070024
Dash	--	--	--	-0.121608	0.8967	0.000173	-0.200902	0.0282**	0.048198	-0.489244	0.0423**	0.041396	-0.561329	0.0321**	0.046037	-0.820837	0.0083***	0.068946
Ethereum	--	--	--	0.214295	0.0821*	0.030531	-0.018381	0.8726	0.000264	0.191028	0.2752	0.012137	-0.041649	0.9374	0.000063	--	--	--
Litecoin	--	--	--	--	--	--	-0.041778	0.6839	0.001699	-0.645444	0.0814*	0.030661	-0.974173	0.0134**	0.060733	--	--	--
NEM	2.541848	0.0009***	0.107116	5.506694	0.0000***	0.225010	6.684510	0.0023***	0.091056	--	--	--	--	--	--	--	--	--
Ripple	-0.470527	0.0446*	0.040523	1.545744	0.0849*	0.029993	7.550174	0.0003***	0.128235	--	--	--	--	--	--	--	--	--

Table 13 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥95 or M≤05 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 14 – Barrier proximity test results for the 90-10 dummy – Cryptocurrencies

	90-10 dummy																	
Cryptocurrency	M0.01			M0.1			M1			M10			M100			M1000		
	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2	β	P-value	R^2
Bitcoin	--	--	--	--	--	--	-0.024301	0.7108	0.001409	-0.045464	0.4290	0.006395	-0.183019	0.0247**	0.050401	-0.669751	0.0006***	0.114671
Dash	--	--	--	0.631401	0.3795	0.007890	-0.061979	0.3831	0.007773	-0.534158	0.0035***	0.083621	-0.457588	0.0227**	0.051842	-0.657520	0.0058***	0.074968
Ethereum	--	--	--	0.045448	0.6336	0.002327	0.072909	0.4069	0.007029	0.409309	0.0019***	0.094422	0.464231	0.2528	0.013320	--	--	--
Litecoin	--	--	--	--	--	--	0.109727	0.1620	0.019855	-0.793198	0.0048***	0.078469	-0.987186	0.0010***	0.105685	--	--	--
NEM	1.232748	0.0392**	0.042694	3.389788	0.0001***	0.144487	3.425739	0.0446**	0.040527	--	--	--	--	--	--	--	--	--
Ripple	-0.607300	0.0006***	0.114393	3.085665	0.0000***	0.202541	3.871402	0.0166**	0.057134	--	--	--	--	--	--	--	--	--

Table 14 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥90 or M≤10 and 0 otherwise (see section 3.2.4.1 for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 15 – Barrier hump test results – ADR

ADR	M1			M10			M100		
	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2
Alibaba	0.000138	0.0153**	0.065869	-1.54E-05	0.7618	0.000974	0.000575	0.0000***	0.333027
Nokia	4.59E-05	0.1560	0.026924	-0.000575	0.0000***	0.575686	--	--	--
Novartis	3.27E-06	0.9052	0.011650	-9.73E-05	0.0039***	0.138839	-0.000425	0.0009***	0.276687
Shell	1.17E-05	0.6919	0.001627	-5.59E-06	0.8494	0.008225	--	--	--
Teva	6.74E-05	0.0421**	0.043547	0.000187	0.0000***	0.375537	--	--	--
Vale	3.32E-05	0.1783	0.018617	-0.000160	0.0000***	0.188277	--	--	--

Table 15 shows the results of a barrier hump test using the regression $f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon$,, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, regressed to the said M-values and the respective squares. (see section 3.2.4.2 for further details). H0: δ=0; H1: δ<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 16 – Barrier hump test results – ETF

ETF	M1			M10			M100		
	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2
Brazil	3.02E-05	0.2834	0.017206	-0.000136	0.0000***	0.191032	--	--	--
Germany	5.37E-05	0.3520	0.009025	-0.000454	0.0000***	0.348509	--	--	--
Japan	-3.26E-05	0.8639	0.002857	0.000169	0.0000***	0.381576	--	--	--
South Africa	-1.64E-06	0.9483	0.015368	1.57E-05	0.5538	0.056561	--	--	--
US: Russell 1000	7.26E-06	0.7731	0.005923	-4.03E-05	0.1048	0.035898	-8.10E-05	0.3837	0.011141
US: S&P 500	7.37E-06	0.7591	0.003005	2.41E-05	0.3865	0.065137	0.000264	0.0001***	0.401576

Table 16 shows the results of a barrier hump test using the regression $f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon$,, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, regressed to the said M-values and the respective squares. (see section 3.2.4.2 for further details). H0: δ=0; H1: δ<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 17 – Barrier hump test results – Cryptocurrencies

Cryptocurrency	M0.01			M0.1			M1			M10			M100			M1000		
	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2	δ	P-value	R^2
Bitcoin	--	--	--	--	--	--	-1.11E-05	0.7567	0.005196	-3.78E-05	0.2298	0.015399	-8.72E-05	0.0398**	0.144512	-0.000399	0.0001***	0.198486
Dash	--	--	--	6.67E-05	0.8660	0.003084	-2.53E-05	0.5153	0.010540	-0.000182	0.0624*	0.110357	-2.55E-05	0.8136	0.063622	-0.000108	0.3873	0.131110
Ethereum	--	--	--	6.28E-05	0.2274	0.023761	2.62E-05	0.5644	0.117718	0.000396	0.0000***	0.334732	0.000631	0.0038***	0.093923	--	--	--
Litecoin	--	--	--	--	--	--	0.000136	0.0006***	0.215011	-0.000513	0.0003***	0.248450	-0.000591	0.0001***	0.289809	--	--	--
NEM	0.000716	0.0225**	0.130263	0.001883	0.0000***	0.264139	0.002225	0.0145**	0.104610	--	--	--	--	--	--	--	--	--
Ripple	-0.000464	0.0000***	0.338939	0.001336	0.0001***	0.308101	0.002405	0.0050***	0.131227	--	--	--	--	--	--	--	--	--

Table 17 shows the results of a barrier hump test using the regression $f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon$,, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, regressed to the said M-values and the respective squares. (see section 3.2.4.2 for further details). H0: δ=0; H1: δ<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

4.3 Conditional Effects Test

Tables 18-20 present the results of the conditional effects test, where we examine the behavior of the selected financial assets' prices in the 5-day periods before and after crossing a barrier from below, constituting a potential resistance level, and also in the 5-day periods before and after crossing a barrier from above, constituting a potential support level. We assess if the return series register a pattern on these days which is significantly different from when prices are not in the proximity of any barrier, as well as if markets calm down or are in turmoil after breaking a barrier.

We perform this test for one potential barrier level only for each asset, chosen as the most likely to constitute an actual barrier level, according to the results from the previous tests. Therefore, regarding ADRs, the conditional effects test is applied to the 10-level barrier for Nokia, Shell, Teva and Vale and to the 100-level barrier for Alibaba and Novartis; concerning ETFs, it is applied to the 10-level barrier for Brazil, Germany, Japan and South Africa and to the 100-level barrier for Russell 1000 and S&P 500; as for cryptocurrencies, this test is applied to the 0.1-level barrier for NEM and Ripple, to the 10-level barrier for Ethereum and Litecoin and to the 100-level barrier for Bitcoin and Dash.

The results of the mean return equation for all the financial assets present in our study are shown in Table 18, where we may observe that the mean return after crossing a barrier from below is positive for all the 18 financial assets – and significant at a 5 percent level for all of them except the Russell 1000 ETF and Litecoin – while before crossing a barrier in such movement it is positive for all assets except the Russell 1000 ETF but only significant at a 5 percent level for 7 of them: the Shell, Vale and Teva ADRs; the Brazil and South Africa ETFs; Bitcoin and Ripple. Still on the upward movements, the results show that the magnitude of returns is higher after crossing a barrier for all assets except Litecoin. The crossing of a barrier from below promotes a change in the signal of the mean returns for 1 asset only: the Russell 1000 ETF.

As for the crossings from above, we observe that the mean return is negative for all assets after crossing a barrier in such movement – significant at a 5 percent level for all assets but the Novartis ADR, the Russell 1000 and S&P 500 ETFs and Ripple – and also negative before crossing the barrier for 16 assets – Dash and Ripple being the exceptions – but only significant at a 5 percent level for 7 of them: the Alibaba, Shell, Teva and Vale ADRs and the Brazil, Germany and South Africa ETFs; curiously, there are no negative and significant mean returns for any of the 6 studied cryptocurrencies in the 5-day periods before crossing a barrier in a downward movement. The magnitude of returns is higher in the 5-day periods after crossing a barrier for all assets except the Russell 1000 and S&P 500 ETFs. The crossing of a barrier in a downward movement promotes a signal change in the mean return of only 2 assets: Dash and Ripple. Even though there are a couple of curious observations about the mean returns of cryptocurrencies in the 5-day periods before and after crossing a barrier from above, overall the results presented in this table show no significant differences between the three categories of financial assets.

Table 19 shows the results of the variance equation. In the presence of psychological barriers, we should find positive variance indicators before crossing a barrier – meaning that the market is turbulent – and negative indicators after crossing a barrier – meaning that the market is calmer. Regarding upward movements, we find positive variance indicators before crossing a barrier for 10 of the 18 financial assets (two ADRs, three ETFs and five cryptocurrencies) and negative indicators after crossing a barrier for 14 assets (four ADRs, five ETFs and five cryptocurrencies). As for downward movements, we find positive indicators before crossing barriers for 13 assets (five ADRs, six ETFs and two cryptocurrencies) and negative indicators after crossing barriers for 12 assets (three ADRs, three ETFs and six cryptocurrencies). We observe that volatility tends to increase after crossing a barrier from below and decrease after crossing a barrier from above which, considering the results obtained for the mean return equation, is in line with the efficient market hypothesis and the theory that to higher returns corresponds higher volatility. The GARCH term is positive and significant at a 1 percent level for every asset, indicating significant GARCH effects. Again, apart from the higher volatility of cryptocurrencies when compared to ADRs and ETFs (see Section 3.1), we do not find significant differences between the three financial markets.

Finally, Table 20 exhibits the results of the Wald test to the hypotheses listed in Section 3.2.5. We find significant (at a 5 percent significance level) changes in the conditional mean returns after crossing a barrier in an upwards movement for three ADRs, two ETFs and two cryptocurrencies (Alibaba, Shell and Teva; Brazil and South Africa; Bitcoin and NEM), while for downwards movements we observe that changes in the conditional mean returns are significant at 5 percent for two ADRs, three ETFs and three cryptocurrencies (Shell and

Vale; Brazil, Germany and South Africa; Bitcoin, Dash and NEM). As for differences in the conditional variance, we observe significant results for the Teva ADR, the Germany ETF and four cryptocurrencies – Bitcoin, Ethereum, Litecoin and NEM – concerning upwards movements and regarding downwards movements we find significant differences for three ADRs, one ETF and three cryptocurrencies, namely: Alibaba, Shell and Teva; Japan; Bitcoin, Ethereum and Ripple.

Summing up, through the conditional effects test we find strong evidence that the magnitude of the mean returns is higher in the 5-day period after crossing a barrier, both for upward and downward movements, and for all three financial markets under study. Also, we observe that markets tend to be turbulent before crossing a barrier and calmer after that barrier is crossed, but results also show that volatility tends to stay aligned with returns, as predicted by the efficient markets hypothesis. Finally, analyzing the results of the Wald test, we observe significant signs of the existence of psychological barriers in the Alibaba, Shell, Teva and Vale ADRs, in the Brazil, Germany, Japan and South Africa ETFs and in all cryptocurrencies: Bitcoin, Dash, Ethereum, Litecoin, NEM and Ripple. Clearly Bitcoin presents the stronger case for the existence of psychological barriers, as all 4 null hypotheses are rejected at a 5 percent significance level.

We are now in position to summarize the results of each test and analyze them jointly, reaching the global results shown in the last column of Table 21, which wraps up the course of our work and presents a final conclusion on whether there is sufficient evidence for psychological barriers in each of the 18 assets under study. We conclude that psychological barriers exist for the assets in which we find consistent evidence of psychological barriers throughout the four tests performed, which is the case of the Vale ADR, the Brazil and Germany ETFs and four cryptocurrencies: Bitcoin, Dash, Litecoin and Ripple.

Table 18 – Conditional effects test results – Return equation

			C	UB	UA	DB	DA
ADR	Alibaba	Coefficient	0.098268	0.054738	1.629865	-0.841781	-1.603396
		P-value	0.1476	0.8073	0.0017***	0.0000***	0.0170**
	Nokia	Coefficient	-0.038175	0.735087	0.909513	-0.234016	-1.529735
		P-value	0.3395	0.0710*	0.0150**	0.6312	0.0005***
	Novartis	Coefficient	0.035420	0.473630	0.708806	-0.264256	-0.485396
		P-value	0.0995*	0.1015	0.0028***	0.3876	0.0736*
	Shell	Coefficient	0.044994	0.377709	0.713207	-0.502567	-0.857853
		P-value	0.0929*	0.0000***	0.0000***	0.0000***	0.0000***
	Teva	Coefficient	0.009702	0.345805	0.745008	-0.429993	-0.701528
		P-value	0.7643	0.0148**	0.0000***	0.0119**	0.0000***
	Vale	Coefficient	-0.007174	0.615956	1.020529	-0.588589	-1.235348
		P-value	0.8868	0.0127**	0.0000***	0.0074***	0.0000***
ETF	Brazil	Coefficient	0.025607	0.368976	0.865468	-0.579249	-1.052926
		P-value	0.4792	0.0053***	0.0000***	0.0001***	0.0000***
	Germany	Coefficient	0.050155	0.178311	0.319704	-0.253088	-0.578489
		P-value	0.2540	0.0811*	0.0000***	0.0061***	0.0000***
	Japan	Coefficient	0.035031	0.126311	0.357707	-0.136169	-0.428006
		P-value	0.0739*	0.1701	0.0000***	0.2949	0.0000***
	South Africa	Coefficient	0.028268	0.275170	0.630293	-0.266712	-0.908052
		P-value	0.4588	0.0112**	0.0000***	0.0140**	0.0000***
	US: Russell 1000	Coefficient	0.067343	-0.084800	0.273766	-0.257115	-0.150318
		P-value	0.0000***	0.9112	0.2005	0.3713	0.8607
	US:S&P 500	Coefficient	0.058073	0.169721	0.204660	-0.120706	-0.050007
		P-value	0.0001***	0.4191	0.0002***	0.6231	0.7796
Cryptocurrencies	Bitcoin	Coefficient	0.047267	0.653231	1.468313	-0.198326	-1.737642
		P-value	0.5462	0.0131**	0.0000***	0.5782	0.0000***
	Dash	Coefficient	0.179519	0.862760	2.562990	0.665292	-3.078990
		P-value	0.2156	0.4316	0.0268**	0.0559*	0.0000***
	Ethereum	Coefficient	0.317918	0.252507	1.392532	-0.124918	-1.633306
		P-value	0.1601	0.6747	0.0049***	0.8291	0.0023***
	Litecoin	Coefficient	-0.141775	2.286960	1.382177	-0.681345	-1.887338
		P-value	0.3025	0.0908*	0.1519	0.5085	0.0086***
	NEM	Coefficient	0.363233	1.063587	5.950540	-1.202191	-5.145693
		P-value	0.1155	0.1095	0.0106**	0.0937*	0.0062***
	Ripple	Coefficient	-0.438762	3.461102	3.979767	1.968350	-1.875886
		P-value	0.0000***	0.0475**	0.0154**	0.4140	0.1406

Table 18 shows the results of the mean equation of a GARCH estimation of the form $R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t$; $\varepsilon_t \sim N(0, V_t)$; $V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. UB, UA, DB and DA are dummy variables. UB takes the value 1 in the 5 days before crossing a barrier from below; UA takes the value 1 in the 5 days after crossing a barrier from below; DB takes the value 1 in the 5 days before crossing a barrier from above; DA takes the value 1 in the 5 days after crossing a barrier from above. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 19 – Conditional effects test results – Variance equation

			C	RESID(-1)^2	GARCH(-1)	UB	UA	DB	DA
ADR	Alibaba	Coefficient	0.755254	0.047838	0.735818	-0.538519	1.092820	-0.963153	1.420579
		P-value	0.0055***	0.0151**	0.0000***	0.0628*	0.2258	0.0000***	0.1180
	Nokia	Coefficient	0.794120	0.126416	0.786544	-1.068457	-0.918012	1.364363	0.750218
		P-value	0.0000***	0.0000***	0.0000***	0.0271**	0.0118**	0.0131**	0.2654
	Novartis	Coefficient	0.022642	0.039725	0.943479	0.074053	-0.178317	0.253564	-0.088289
		P-value	0.0000***	0.0000***	0.0000***	0.6242	0.2170	0.1491	0.6097
	Shell	Coefficient	0.019116	0.055834	0.930105	-0.064306	0.013377	0.345394	-0.141825
		P-value	0.0000***	0.0000***	0.0000***	0.0636*	0.6760	0.0000***	0.0120**
	Teva	Coefficient	0.010235	0.014946	0.979558	0.142860	-0.162178	1.168931	-1.061546
		P-value	0.0013***	0.0000***	0.0000***	0.0002***	0.0000***	0.0000***	0.0000***
	Vale	Coefficient	0.050985	0.049789	0.942943	-0.227532	-0.245303	0.437305	0.205659
		P-value	0.0037***	0.0000***	0.0000***	0.1604	0.1044	0.0431**	0.3239
ETF	Brazil	Coefficient	0.043810	0.071461	0.908763	0.040846	-0.110887	0.392342	0.198513
		P-value	0.0000***	0.0000***	0.0000***	0.6909	0.2017	0.0002***	0.1374
	Germany	Coefficient	0.034708	0.049227	0.886911	0.092384	-0.126743	0.124960	0.127375
		P-value	0.0015***	0.0000***	0.0000***	0.0035***	0.0000***	0.0018***	0.0107**
	Japan	Coefficient	0.013538	0.091780	0.901165	-0.008875	-0.056479	0.188648	-0.045860
		P-value	0.0000***	0.0000***	0.0000***	0.7387	0.0948*	0.0000***	0.2944
	South Africa	Coefficient	0.069537	0.082081	0.896754	-0.101565	-0.128454	0.114806	0.254938
		P-value	0.0001***	0.0000***	0.0000***	0.1055	0.0288**	0.1286	0.0005***
	US: Russell 1000	Coefficient	0.060451	0.251643	0.713280	0.757224	-0.178804	0.178404	-0.737732
		P-value	0.0000***	0.0000***	0.0000***	0.4250	0.0000***	0.4187	0.4391
	US:S&P 500	Coefficient	0.016131	0.108070	0.876383	-0.050087	-0.047696	0.322973	-0.095403
		P-value	0.0000***	0.0000***	0.0000***	0.1595	0.0495**	0.0239**	0.3952
Cryptocurrencies	Bitcoin	Coefficient	0.305429	0.119209	0.841295	2.098793	-1.385855	2.897624	-0.981315
		P-value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0051***
	Dash	Coefficient	2.170309	0.209140	0.756723	11.27698	8.533534	-5.271212	-6.572060
		P-value	0.0000***	0.0000***	0.0000***	0.0021***	0.0214**	0.0405**	0.0073***
	Ethereum	Coefficient	3.146808	0.274855	0.660830	7.437283	-0.339366	-4.436034	-0.434693
		P-value	0.0000***	0.0000***	0.0000***	0.0000***	0.8561	0.0000***	0.6087
	Litecoin	Coefficient	1.823726	0.091578	0.848421	42.70457	-22.82108	-1.386583	-1.919355
		P-value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.3691	0.1763
	NEM	Coefficient	20.01924	0.436817	0.356497	-2.700916	83.05120	-19.26134	-8.614527
		P-value	0.0000***	0.0000***	0.0000***	0.3486	0.0000***	0.0000***	0.4938
	Ripple	Coefficient	6.523490	0.757406	0.339212	26.08747	-1.325158	58.35800	-0.771086
		P-value	0.0000***	0.0000***	0.0000***	0.1615	0.9389	0.0669*	0.9360

Table 19 shows the results of the variance equation of a GARCH estimation of the form $R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t;\ \ \varepsilon_t \sim N(0, V_t);\ V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. UB, UA, DB and DA are dummy variables. UB takes the value 1 in the 5 days before crossing a barrier from below; UA takes the value 1 in the 5 days after crossing a barrier from below; DB takes the value 1 in the 5 days before crossing a barrier from above; DA takes the value 1 in the 5 days after crossing a barrier from above. V_{t-1} refers to the moving average parameter and ε_{t-1}^2 stands for the GARCH parameter. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 20 – Conditional effects test results – Wald test

			H1	H2	H3	H4
ADR	Alibaba	Chi-square	7.987701	1.257374	2.705687	5.859107
		P-value	0.0047***	0.2621	0.1000	0.0155**
	Nokia	Chi-square	0.107295	3.618560	0.041723	0.346069
		P-value	0.7432	0.0571*	0.8381	0.5563
	Novartis	Chi-square	0.518942	0.279099	0.842203	1.163688
		P-value	0.4713	0.5973	0.3588	0.2807
	Shell	Chi-square	7.890146	5.583205	1.572920	20.39569
		P-value	0.0050***	0.0181**	0.2098	0.0000***
	Teva	Chi-square	5.692545	1.353626	17.54659	705.7751
		P-value	0.0170**	0.2446	0.0000***	0.0000***
	Vale	Chi-square	1.784927	4.488522	0.003480	0.315239
		P-value	0.1815	0.0341**	0.9530	0.5745
ETF	Brazil	Chi-square	6.941413	5.391169	0.733350	0.755215
		P-value	0.0084***	0.0202**	0.3918	0.3848
	Germany	Chi-square	1.313048	5.704932	15.89074	0.000923
		P-value	0.2518	0.0169**	0.0001***	0.9758
	Japan	Chi-square	3.749489	3.315477	0.747405	9.965640
		P-value	0.0528*	0.0686*	0.3873	0.0016***
	South Africa	Chi-square	6.971810	17.11480	0.063370	1.105527
		P-value	0.0083***	0.0000***	0.8012	0.2931
	US: Russell 1000	Chi-square	0.204418	0.014060	0.978784	0.864794
		P-value	0.6512	0.9056	0.3225	0.3524
	US:S&P 500	Chi-square	0.025945	0.052968	0.001618	2.968178
		P-value	0.8720	0.8180	0.9679	0.0849*
Cryptocurrencies	Bitcoin	Chi-square	4.254905	10.06125	69.02390	33.26345
		P-value	0.0391**	0.0015***	0.0000***	0.0000***
	Dash	Chi-square	1.017019	27.60466	0.157684	0.089715
		P-value	0.3132	0.0000***	0.6913	0.7645
	Ethereum	Chi-square	1.373954	1.973282	5.393553	6.867278
		P-value	0.2411	0.1601	0.0202**	0.0088***
	Litecoin	Chi-square	0.287240	0.915199	150.6705	0.040390
		P-value	0.5920	0.3387	0.0000***	0.8407
	NEM	Chi-square	4.221587	4.078832	20.12859	0.728248
		P-value	0.0399**	0.0434**	0.0000***	0.3935
	Ripple	Chi-square	0.039967	2.315739	0.956100	3.117833
		P-value	0.8415	0.1281	0.3282	0.0774**

Table 20 shows the results of a Wald test to four hypotheses. H1: There is no significant difference in the conditional mean return before and after an upwards crossing of a barrier; H2: There is no significant difference in the conditional mean return before and after a downwards crossing of a barrier; H3: There is no significant difference in the conditional variance before and after an upwards crossing of a barrier; H4: There is no significant difference in the conditional variance before and after a downwards crossing of a barrier. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 21 – Summary of results from the various tests

		Uniformity	Barrier proximity	Barrier hump	Conditional effects	Psychological barriers?
ADR	Alibaba	Yes	No	No	Yes	No
	Nokia	Yes	Yes	Yes	No	No
	Novartis	Yes	Yes	Yes	No	No
	Shell	Yes	No	No	Yes	No
	Teva	Yes	No	No	Yes	No
	Vale	Yes	Yes	Yes	Yes	Yes
ETF	Brazil	Yes	Yes	Yes	Yes	Yes
	Germany	Yes	Yes	Yes	Yes	Yes
	Japan	Yes	No	No	Yes	No
	South Africa	Yes	No	No	Yes	No
	US:Russell 1000	Yes	Yes	No	No	No
	US:S&P 500	Yes	No	No	No	No
Cryptocurrencies	Bitcoin	Yes	Yes	Yes	Yes	Yes
	Dash	Yes	Yes	Yes	Yes	Yes
	Ethereum	Yes	No	No	Yes	No
	Litecoin	Yes	Yes	Yes	Yes	Yes
	NEM	Yes	No	No	Yes	No
	Ripple	Yes	Yes	Yes	Yes	Yes

Table 21 presents a summary of the results from the four tests performed throughout our work and a final conclusion on the existence of psychological barriers for each of the assets under study. We conclude that psychological barriers exist for the assets in which we find signs of the existence of psychological barriers in all the performed tests. Based on Lim and Lim (2013).

5 Conclusion

The main aim of our work was to extend the study of psychological barriers to unexplored financial assets, assessing whether psychological barriers do or do not exist in the American Depositary Receipts, Exchange-Traded Funds and Cryptocurrencies markets. Moreover, our study intended to analyze the different investor profiles of each of the financial assets under study and subsequently examine if there is any seeming connection between the investor profiles and the existence or non-existence of psychological barriers in each market. To the best of our knowledge, this work is the first applying the study of psychological barriers to the above-mentioned markets, as well as the first trying to relate the different investor profiles to the susceptibility to psychological barriers, which gives us the opportunity to fill a gap in the financial literature.

In order to reach our goals, we set a diversified sample composed by 6 of the most liquid assets of each financial market, collected the daily quotes for each of those assets in the last 10 years (2008-2017) and put that sample through a battery of tests, following the methodology of Aggarwal and Lucey (2007). After analyzing the range of each asset's quotes and defining all potential psychological barriers, we started by performing a uniformity test, observing that all assets rejected the null hypothesis, which claimed that the respective M-values followed a uniform distribution. Then, we conducted a barrier proximity test using several intervals to each of the previously defined potential barrier levels, finding signs of the existence of psychological barriers in three ADRs, three ETFs and four cryptocurrencies. The following test was a barrier hump test, which focused on the whole shape of the M-values distribution, assessing if they follow a uniform distribution or a hump-shape distribution – as should be the case in the presence of psychological barriers – and it confirmed the majority of the previous test's results, with the exception of one ETF. Finally, we executed a conditional effects test, in its three modalities: mean return equation, variance equation and hypotheses test. The mean return equation showed us that in all financial markets the magnitude of the mean returns tends to be higher in the 5-day period after crossing a barrier, both for upward and downward movements; the variance equation led to the observation that markets are turbulent before crossing a barrier and calmer afterwards; through the hypotheses test, we observed signs of the existence of psychological barriers in three ADRs, three ETFs and four cryptocurrencies.

Analyzing the results of all tests jointly, we find significant and consistent evidence of the existence of psychological barriers for the Brazil and Germany ETFs, as well as for four cryptocurrencies: Bitcoin, Dash, Litecoin and Ripple. Regarding ADRs, we find evidence of the existence of barriers for Vale and inconclusive results for the remaining assets, as the barrier tests show signs of psychological barriers for Nokia and Novartis, while the conditional effects test shows stronger signs of barriers for Alibaba, Teva and Shell.

Among all the 18 assets under study, Bitcoin – the *quasi-monopolist* leader of the cryptocurrencies market – is by far the one who presents stronger evidence of the existence of psychological barriers as, for the 100-level barrier, the null hypotheses of the uniformity, barrier proximity and barrier hump tests, as well as the four null hypotheses of the conditional effects test, were all rejected at a 5 percent significance level.

Comparing the three studied financial markets, we observe that the cryptocurrencies market – which has the highest prevalence of individual investors – is the one where we find more assets evidencing the existence of psychological barriers (4 out of 6 assets under study), followed by Exchange-Traded Funds (2 out of 6) and American Depositary Receipts (1 out of 6) – both with a high percentage of experienced traders. This observation, along with the strong evidence obtained for Bitcoin, may lead us to the conclusion that unexperienced investors are more prone to the behavioral biases which cause psychological barriers than professional traders. This apparent conclusion must be considered very carefully, as a sample composed of assets from only 3 financial markets is too narrow for such an important claim; even so, we believe that the results of this ground-breaking work leave an appealing seed for future research on the relationship between investor profiles and psychological barriers

The conclusions of our work, as well as the specific results of the conditional effects test through the mean return and variance equations, may potentially be used by investors to build more profitable strategies when in presence of psychological barriers. Moreover, concerning the impact on the efficient market hypothesis, we believe that markets are not efficient, for these findings suggest the existence of psychological barriers in the financial markets under study which, as stated by Dorfleitner and Klein (2009), is not compatible with market efficiency, as well as with the assumption of rational investors.

Our study certainly has various limitations which may lead to future research on this topic. Regarding each market, studies with broader samples could lead to stronger results;

concerning the specific market of cryptocurrencies and its particularities, it could be fruitful to divide the price series into their various phases of different growth rates and volatilities and compare them, analyzing if the existence of psychological barriers and/or the level of such barriers has changed through time; finally, as already mentioned, the results of our work must pave the way for further research and broader analyses on the relationship between investor profiles and psychological barriers.

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